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Achieving sustainable structural steel design by estimating fabrication labor cost based on BIM data

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Abstract

Structural steel is heavily utilized in the construction industry from residential and commercial buildings to oil and gas projects. For steel fabrication companies as suppliers of steel structures, submitting competitive project bids requires substantial knowledge of the company's practices on the shop floor and extensive experience to interpret that into credible cost estimations. Being able to make reliable estimates would contribute to the company's competitiveness in the long run. In this study, the total quantity of worker-hours or man-hours required for each major subdivision of a project is considered as the variable of interest in estimating a steel fabrication project, mainly because of the labor-intensive nature of steel fabrication. In collaboration with a partner company, three years of project data, were collected by matching the company's building information modeling (BIM) system with their labor costing system resulting in over 3,000 records, each representing the quantity takeoff for 46 design features and the worker-hours expended in shop fabrication. Stepwise regression and error analysis are used to recognize the most crucial design features in estimating project worker-hours, allowing discovery of the minimized set of inputs for estimating worker-hours and characterization of the estimation uncertainties. This labor cost estimation benefits estimators and shop production planners in that they can configure labor resources to deploy, schedule shop floor production, and recognize estimates' associated errors, based on the company's historical data. This study is an example of using BIM data and providing tools for structural engineers to consider steel fabrication and possibly achieve more sustainable designs.

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Keywords: Steel fabrication; Construction industry; Regression analysis; Worker-hour estimation;

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1. Introduction

In the construction industry, fabricated steel pieces comprise one of the main materials required in typical construction processes [1]. The fabrication process of steel pieces and components encompasses operations of cutting, fitting, welding, and surface processing, which are highly dependable on fabrication setup and crew experience. A confident prediction of fabrication man-hours or worker hours is essential for estimating steel fabrication costs and planning the processes [2]. As a result of labor-intensive nature of steel fabrication, costs for supporting facilities, resources, equipment, wastes and fabrication overhead are generally treated as indirect costs which are correlated to the direct labor costs [2]. There are many types of work and quantities of components, connections and handling involved in steel fabrication projects (e.g. weight, length, weld length, etc.), which need to be translated into worker-hours required to execute a certain project.

BIM has been commonly used in the past decade as a collaborative platform for designing a structure and virtually simulating the construction process. BIM is being adopted in the steel fabrication industry as it offers great advantages from constructability reviews to material quantity takeoffs. There are many long-term incentives in adopting BIM at the company level, such as effective information management. Every steel fabrication project has specific details that give the main indicators of project complexity and difficulty, along with worker-hours and duration it would take to deliver the project in the fabrication shop. Therefore, the project details can be used as predictors in project worker-hours estimation. Project details can be efficiently obtained from BIM models, which can be used as inputs for worker-hour estimation. Thus, the company's historical data could be utilized in developing a data-driven prediction model with project details as its inputs and project worker-hours as the output.

It is a commonly accepted fact that the design stage of the projects presents a great opportunity to consider sustainability concepts to influence construction costs and project life cycle. However, the decision support tools to inform the designers on project performance and sustainability in the early stages of projects have not been fully explored [3]. Guggemos et al. [4] studied the possible enhancements to design and fabrication processes of steel structures to improve their sustainability. In this research, lack of direct communication between the structural team (structural engineer, steel detailer, fabricator, etc.) and early involvement of fabricators in the steel design process are identified as the main areas requiring improvement. Weisenberger [5] studied sustainability in steel structures from a structural engineers' perspective and concluded that a green structural system is not only about the material but also the cooperative design process. BIM, as a collaborative environment, could be used to develop BIM-based tools that take advantage of the information stored and focus on sustainability and resource utilization [5].

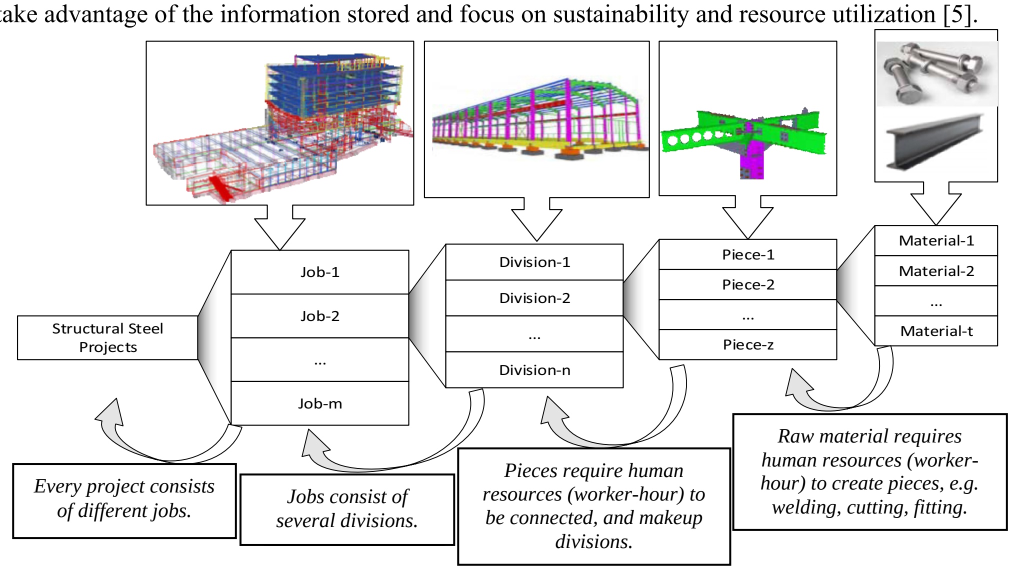

Fig. 1. Steel fabrication project's database structure

The partner company's information system architecture is represented in Figure 1. It is not always economical for companies to track every detail of labor productivity in terms of worker-hours vs. work completed in the real-world project control systems. Many companies capture labor productivity information only at the level sufficient to cater to the requirements of the owners. In the case study, as projects are delivered by *divisions* for billing purposes, the worker-hours required for each particular project are recorded at the level of divisions and stored in project labor cost databases. Although this "broad-brush" information presents limitations in establishing a solid connection between component-centric BIM data and productivity indicators, data-mining techniques still hold the potential to decode the correlation between division component details (from BIM) and worker-hours (from labor cost databases) (Fig. 1). To achieve this goal, regression techniques have been investigated for developing a model between input factors (division material details) and the output (division worker-hours).

In this paper, a brief review of recent applications of BIM in estimation and quantity takeoff in construction management is provided. Next, Multiple Linear Regression (MLR) and its applications as a predictive model in construction management is reviewed. In the following section, an overview of variable selection methods and a framework for stepwise regression is proposed to clarify the variable selection method proposed in this study. In order to deepen the understanding of the proposed methodology, a practical case study is presented and the results of applying MLR stepwise on collected BIM data are discussed.

2. Literature Review

The first step in cost estimation is a reliable and accurate quantity takeoff. There are several common ways to perform quantity takeoff in construction projects. One of the traditional methods is to get the quantity takeoff by counting different materials on 2D drawings and storing the obtained information into spreadsheets [6]. The manual quantity takeoff methods are not able to detect any discrepancies between the 2D drawings, which might result in defective estimates [7]. In comparison, BIM models are great tools for quantity takeoffs, to avoid facing the limitations of 2D drawings [8]. There are many studies addressing quantity takeoff and estimation capabilities of BIM [6],[7],[8],[9]. Shen and Issa [7] studied BIM-based construction estimation and the impact of visualization on estimation accuracy. Monterio and Poças Martins [8] demonstrated the possibility of extracting BIM model quantities with some adjustments to the model prepared for visualization or drawing applications. Plebankiewicz et al. [9] investigated BIM-based cost estimating systems, and it was concluded that BIM applications are able to generate accurate quantity takeoffs, but there is a gap in connecting these material quantities directly to labor and equipment costs. Hu et al. [6] used extracted data from a BIM model and generated a linear regression model with all BIM features for estimating steel fabrication man-hours. From the literature review on this subject, the combination of data mining techniques with BIM quantity takeoffs was found to be missing. Features captured from BIM models could be numerous, and having all the features in a regression model would not be the proper approach, as discussed in the following sections.

Regression analysis is a powerful tool to model a complicated real-world system and predict the system behavior based on a set of independent variables [10]. While being computationally inexpensive, regression analysis allows researchers to gain more knowledge about variables' relationships in examining data [11], [12]. Regression analysis techniques have found numerous applications in construction management, mainly to create predictive or explanatory models, attempting to transfer information into knowledge [13], [14]. One of the main advantages of regression analysis compared to other data-mining techniques is its transparency and ease of use. MLR is one of the regression techniques where two or more independent variables are used to predict a dependent variable. Lowe et al. [15] developed a linear regression model to predict building construction cost. El-abbasy et al. [16] formed a service condition assessment model for oil and gas pipelines based on historical data collected from existing pipelines. Jafarzadeh et al. [17] utilized MLR to predict seismic retrofit construction cost and develop a predictive model. The literature review has revealed the widespread use of MLR in the construction field. Despite that, in all the reviewed studies, regression variable selection is dealt with through statistical software packages, while a clear explanation of the process is absent in general.

3. Methodology

The main challenge of prediction models is to select a proper set of variables as predictors (X_i) of the dependent variable (Y). Selecting a subset of variables instead of including all the variables has statistical and practical advantages in addition to simplicity. From the statistical perspective, minimizing the number of parameters would significantly reduce the chance of over-fitting, collinearity, and transferring noise of data into the resulting model. On the other hand, being able to make estimates using fewer input variables is favorable from the practical point of view and would also reduce data collection efforts. When too many variables are used with the least square method, the model begins finding ways to fit itself to not only underlying patterns of the training set, but to the noises hidden in the training set as well, which is one way to explain why too many features generally lead to poor prediction results. By using stepwise regression, it is possible to remove the relatively insignificant input variables and avoid over-fitting models. Reducing the number of parameters and yet being able to produce reliable results would eventually streamline the data collection efforts while reducing possible noise included in the real-world data.

Reducing the number of independent variables, also known as variable selection, is commonly related to applying several methods such as Factor Selection, Forward Selection (FS), Backward Elimination (BE), and Stepwise Regression. The main objective of these methods is to predict an output variable by a subset of input variables while retaining all or most of the explanatory power of the full set of variables [12]. For a MLR model with n predictors, there are 2^n possible subsets of variables, making it practically infeasible to examine them all [17]. Stepwise regression, while identifying significant input variables, eliminates multicollinearity between variables. It is noted multicollinearity refers to the scenario when the MLR predictors are correlated to one another; in other words, they can be explained by each other [18].

MLR models are capable of making point value estimates for a given set of input parameters; however, they generally would not be able to give any identification of the estimation errors. MLR model estimations include uncertainties from both regression variables and regression fitting process [19]. To address those uncertainties, statistics provide a confidence interval (CI) which represents a range of values for the MLR point value estimate. In other words, CI provides the information on the expected value of a dependent variable in connection with a probability defined as the confidence level. The objectives of this methodology, to (1) formulate the simplified regression model based on stepwise regression technique, and (2) establish the confidence interval around the model's point-value prediction, are discussed. The stepwise regression procedure, explained in the following steps, has the aim of identifying proper input variables for predicting the output variable.

In Step 1, the variables are separated into two sets, namely: (I) selected set $\{x_{i,sel}\}$ and (II) remained set $\{x_{i,rem}\}$. Variables included in the selected set $\{x_{i,sel}\}$ will be used to formulate the regression model. The variables in the remained set $\{x_{i,rem}\}$ are those that have not yet been tested or have been removed from the model due to their low significance. Note that all independent variables are initialized in the remained set while the selected set is null.

Variables included in the regression model, selected set $\{x_{i,sel}\}$, should be regarded as controlling variables for the remained set. In Step 2, the correlation coefficients measure the degree of association between output (i.e. y) and remained variables (i.e. $\{x_{i,rem}\}$), with the effect of controlling variables (i.e. $\{x_{i,sel}\}$) removed. If the selected set is null (e.g. first iteration) the correlation coefficient is determined as Pearson's correlation coefficient $r_{x_{i,rem}y}$ (Eq. 1) [20]. If there are variables in the selected set, partial correlation coefficient $r_{x_{i,rem}y\cdot\{x_{i,sel}\}}$ is calculated given the variables in the selected set as controlling variables (Eq. 2). The correlation coefficient measures the correlation between each independent variable x and response variable y. The numerical boundaries of the coefficient are between [+1, −1]. A positive value indicates that the variables are positively correlated and a negative value means that the variables are negatively correlated. The magnitude of the value shows the strength of correlation [21].

$$\text{If}\{x_{i,sel}\} = \phi\,,\; r_{\{x_{i,rem}\}y} = \frac{\sum_n [(x_n - \bar{x})(y_n - \bar{y})]}{\sqrt{\sum_n (x_n - \bar{x})^2}\sqrt{\sum_n (y_n - \bar{y})^2}}\text{, for each } \{x_{i,rem}\} \tag{1}$$

$$\text{If}\{x_{i,sel}\} \neq \phi\,,\; r_{\{x_{i,rem}\}y\cdot\{x_{i,sel}\}} = \frac{r_{\{x_{i,rem}\}y} - r_{\{x_{i,sel}\}y} \times r_{\{x_{i,rem}\}\{x_{i,sel}\}}}{\sqrt{1 - r^2_{\{x_{i,rem}\}\{x_{i,sel}\}}}\sqrt{1 - r^2_{\{x_{i,sel}\}y}}}\text{, for each } \{x_{i,rem}\} \tag{2}$$

Where n is the number of data records, x and y are the values of independent and response variables in the dataset, $\bar{x}$ and $\bar{y}$ are the mean values of independent and response variables.

After calculating the correlation coefficients, the variable with the highest correlation coefficient is moved from $\{x_{i,rem}\}$ to $\{x_{i,sel}\}$ in Step 3. This means the selected variable would be included in the regression model so its significance can be evaluated in the next steps.

In Step 4, the regression model is formulated using all the variables stored in $\{x_{i,rem}\}$. By having the regression model, a partial F-test can be performed to calculate the *p-value* $(P_{partial})$ for every variable in $\{x_{i,sel}\}$. The partial F-test measures the significance of independent variables by comparing two regression models, namely: (I) the regression model prior to adding the independent variables, and (II) the regression model after adding the independent variables. The F-statistic (F_{x_i}), which is associated with variables in $\{x_{i,sel}\}$, is calculated based on the error sum of squares (*SSE*) (Eq. 3) with respect to degrees of freedom of the two regression models [20].

$$SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{3}$$

where y_i is the dependent variable (given in the dataset) and $\hat{y}_i$ is the predicted value of regression model

Step 5 is to perform the partial F-test. The F-statistic $(F_{x_i})$is determined by Eq. (4). The *SSE* values for regression models before adding x_i and after adding x_i are computed, respectively: (I) SSE_{k-1,x_i}, represents the *SSE* before adding the independent variable with (n-k) degrees of freedom, and (II) SSE_k represents the SSE after adding the independent variable with (n-k-1) degrees of freedom. In both cases, n is the number of records in the dataset, k is the number of independent variables after adding x_i to the regression model, i.e. the number of variables in $\{x_{i,sel}\}$. Note that the effect of degrees of freedom before and after adding x_i is considered by dividing the nominator and denominator by the degree of freedom. The p-value is determined using right-tailed F-distribution of the partial F-test (Eq. 4) [21].

$$F_{x_i} = \frac{(SSE_{k-1,x_i} - SSE_k)/(1)}{(SSE_k)/(n-k-1)}\text{, for each } x_i \in \{x_{i,sel}\} \tag{4}$$

In Step 6, based on the calculated p-values in Step 5 for the variables included in the model $\{x_{i,sel}\}$, the significance of each variable in formulating the regression model can be measured. The significance level of 0.05 is chosen in this research study as an indicator of significance for removing variables. If a variable/variables deemed not to be significant, it/they should be removed from the regression model by moving them from selected set $\{x_{i,sel}\}$ to the remained set $\{x_{i,rem}\}$.

Stopping criteria are given to allow the variables to be used for formulating the regression model if the variable satisfies the predefined level of significance. In iteration, if the variable x_i with the highest correlation, identified as the highest correlated variable, does not satisfy the required level of significance, the stepwise regression ends in that iteration. In other words, if a variable is selected for formulating the regression model, and after testing the variable is identified as not significant enough to be kept in the model (*p-value* <0.05), the iteration stops.

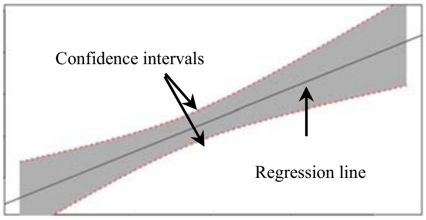

Fig. 2. Regression confidence interval

The developed regression model is capable of predicting the output variable based on new inputs. This point-value estimate includes a certain level of uncertainty due to both regression errors and observation errors (Fig. 2). This study further quantifies the uncertainty of a point-value estimate by defining a confidence interval around the point-value estimates. From the statistical standpoint, the confidence interval for a point value estimate of a linear regression model is defined by Eq. (5) in consideration to the MLR model standard error (*s.e.*) [19].

$$\hat{y}_0 \pm t_{(\alpha/2,n-k-1)} \times s.e. \tag{5}$$

Where $\hat{y}_0$ is the estimate from regression model, $t_{(\alpha/2,n-k-1)}$ is the T-distribution with significance of α (degrees of freedom of n-k-1). s.e. could be obtained from Eq. 6 [19].

$$s.e. = \sqrt{\sigma_f^2} = \sqrt{\sigma_{res}^2 [x_0]([x]^T [x])^{-1} [x_0]^T} \tag{6}$$

Where $([x]^T [x])^{-1}$ is the covariance matrix resulted from historical data, $[x_0]$ formatted in $[1 \quad x_{01} \quad \cdots \quad x_{0k}]$ is the point at which the confidence interval needs to be measured and σ_{res}^2 is the residual standard deviation that is measured by Eq. 7 [19].

$$\sigma_{res}^2 = \frac{SSE}{n-k-1} \tag{7}$$

To account for the extra uncertainty as a result of introducing the new observations for formulating the regression model, the standard deviation of the prediction (σ_p) is calculated based on Eq. (8) [19].

$$\sigma_p = \sqrt{\sigma_{res}^2 + \sigma_f^2} \tag{8}$$

The prediction interval is similarly calculated as $\hat{y}_0 \pm t_{(\alpha/2,n-k-1)} \times \sigma_p$ [19].

4. Case study

The proposed methodology for variable selection is applied in correlating BIM data and productivity data collected from the partner company. Project information obtained from BIM contains 46 design features and about 3000 records each denoting a division of fabrication. Ten input variables are listed in Table 1. In the next step, worker-hours spent on the division level from these projects were matched as the output parameter of the regression model. The proposed stepwise regression approach was applied to identify the most relevant design features for estimating project worker-hours, giving rise to the minimized quantity of inputs for estimating steel fabrication labor cost. Although all these variables are considered important, there are certain inter-correlation (multicollinearity) between them, which means some variables can be described and accounted by others. The proposed methodology is instrumental in removing these inter-correlations in an analytical fashion. For instance, plate length and steel weight are highly correlated; knowing one of them, the other one can be estimated. Therefore, between plate length and weight, only the one that has a higher impact on the output parameter (i.e. actual worker-hours) was factored into the model through the stepwise regression.

Table 1: Part of initial parameters introduced to the stepwise regression model

Variables No.	Parameter Description	Unit of Measurement	Labels
1	Steel Weight	Weight (ton)	x_1
2	Complete Penetration Weld	Length (m)	x_2
3	Partial Penetration Weld	Length (m)	x_3
4	Hex Type Bolts	Quantity (count)	x_4
5	I-Beam	Length (m)	x_5
6	Square Hollow Steel Sections	Length (m)	x_6
7	Round Hollow Steel Sections	Length (m)	x_7
8	Plate	Length (m)	x_8
9	M Type Bolts	Quantity (count)	x_9
10	Wide Flanged Beams	Length (m)	x_{10}
	Actual Worker-hours	Worker-hours (hours)	y

With data available for the input variables (X1 to X46) [6], the proposed stepwise regression method was implemented in order to streamline the input parameters required for estimating labor cost. Setting the significance level for removing a parameter as 0.05, five variables were selected as predictors (Table 2). The resulting regression equation is presented as Eq. 9.

Table 2: Stepwise regression summary

Model	Variables included in the model	R^2	Std. Error of the Estimate	Change Statistics	
				R^2 Change	F Change
1	(*Constant*), x_1	0.492	597.94	0.492	1299.30
2	(*Constant*), x_1, x_2	0.678	475.99	0.186	776.19
3	(*Constant*), x_1, x_2, x_7	0.682	473.70	0.003	14.01
4	(*Constant*), x_1, x_2, x_7, x_5	0.684	472.35	0.002	8.63
5	(*Constant*), x_1, x_2, x_7, x_5, x_4	0.686	471.21	0.002	7.51

$$y = 60.29 + 0.02x_1 + 11.28x_2 + 0.63x_7 + 8.41x_5 + 0.06x_4 \tag{9}$$

Where y is the predicted worker-hours, x_1 is the steel weight in division, x_2 is the complete penetration weld length, x_7 is round hollow sections, x_5 is I-beam, and x_4 is hex type bolts.

Using the developed regression model, a confidence interval for each point value estimate can be identified. For instance, a division has the steel weight of 33070 (ton), the complete penetration weld length of 49.2 (m), round hollow sections of 54 (m), I-beam length of zero, and 962 hex type bolts. Then, the predicted worker-hours for such a division from Eq.9 would be 1301.31 worker-hours. With 95% confidence, the confidence interval for this point estimate would be ± 274.7 worker-hours, which is calculated through Eq.5 to Eq.8 based on the covariance matrix of the dataset and the residual standard deviation of the regression model.

5. Conclusion

Structural steel fabricators act as one of the most important resource suppliers in the construction industry. Labor-intensive characteristics of steel fabrication processes make the worker-hour estimation crucial in project cost estimation. Tapping into database systems where details of steel projects are efficiently stored, regression techniques can be utilized to correlate worker-hours with project details. In such cases, projects have numerous details, which can be inter-correlated or unnecessary in regression modeling. To identify significant variables from the list of project details, stepwise regression methodology is proposed in this study and its application based on data sourced from the BIM database and the labor cost database of the partner company demonstrated promising capabilities. The developed regression model coupled with error analysis would be able to give point estimates while building a confidence interval around the predicted point estimate. Further research in this direction would be to incorporate the worker-hours estimation model into the design stage of the project inside the BIM platforms, giving the designers the ability to compare different design alternatives and propose more sustainable designs.

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